Image compression using wavelet transform

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Abstract:

There are a number of problems to be solved in image compression to make the process viable and more efficient. A lot of work has been done in the area of wavelet based lossy image compression. So the proposed methodology of this paper is to achieve high compression ratio in images using 2D-daubechies Wavelet Transform by applying global threshold for the wavelet coefficients

The proposed work is aimed at developing computationally efficient and effective algorithms for lossy image compression using wavelet techniques, where This paper proposes a modified simple but efficient calculation schema for 2D-daubechies wavelet transformation in image compression. The work is particularly targeted towards wavelet image compression using daubechies Transformation with an idea to minimize the computational requirements by applying global compression threshold for the wavelet coefficients and to improve the quality of the reconstructed image. The promising results obtained concerning reconstructed images quality as well as preservation of significant image details. The numerical results have been presented by using matlab programming.

الخلاصة:

هناك العديد من المسائل التي يجب حلها في مجال ضغط الصور لجعل العملية ملائمة أكثر وأكثر فعالية. وان الكثير من العمل أنجز في حقل التحويل المويجي لضغط الصور. المنهج المقترح في هذا البحث للحصول على نسبة ضغط عالية للصور هي باستخدام تحويل دوبشيز ثنائي الأبعاد وتطبيق دالة عتبة شاملة على جميع معاملات التحويل المويجي .العمل المقترح يهدف إلى تطوير الفعالية الحسابية وزيادة كفاءة خوارزمية ضغط الصور باستخدام التحويل المويجي . إذ اقترح في البحث تعديل بسيط إلا انه فعال في انجاز ضغط الصورة باستخدام تحويل دوبشيز ثنائي الأبعاد .هذا العمل وجه بشكل بارز باتجاه ضغط الصور باستخدام تحويل دوبشيز كفكرة تضمن تقليل المتطلبات الحسابية بواسطة تطبيق دالة عتبة شاملة لمعاملات التحويل المويجي مع تحسين لنوعية الصورة المسترجعة. أحرزت النتائج المرجوة فيما يتعلق بنوعية الصورة مع الاحتفاظ بالتفاصيل الهامة للصورة .أنجزت النتائج باستخدام برنامج الماتلاب.

1- Introduction:

Images contain large amounts of information that requires much storage space, large transmission bandwidths and long transmission times. Therefore it is advantageous to compress the image by storing only the essential information needed to reconstruct the image [Lees2002].Wavelet analysis is very powerful and extremely useful for compressing data such as images and a lot of work has been done in the area of wavelet based lossy image compression [Morton&Petrson1997;Mulcahy; Al-Abudi&George2005 Adams&Patterson 2006; Raviraj&Sanavullah2007] , It's power comes from its multiresolution. Although other transforms have been used, for example the DCT was used for the JPEG format to compress images, wavelet analysis can be seen to be far superior, in that it doesn't create 'blocking artifacts'. This is because the wavelet analysis is done on the entire image rather than sections at a time.

Wavelet analysis can be used to divide the information of an image into approximation and detail subsignals. The approximation subsignal shows the general trend of pixel values, and three detail subsignals show the vertical, horizontal and diagonal details or changes in the image. If these details are very small then they can be set to zero without significantly changing the image. The value below which details are considered small enough to be set to zero is known as the threshold. The greater the number of zeros the greater the compression that can be achieved. The amount of information retained by an image after compression and decompression is known as the " energy retained" and this is proportional to the sum of the squares of the pixel values. If the energy retained is 100% then the compression is known as lossless, as the image can be reconstructed exactly. This occurs when the threshold value is set to zero, meaning that the detail has not been changed. If any values are changed then energy will be lost and this is known as lossy compression. Ideally, during compression the number of zeros and the energy retention will be as high as possible. However, as more zeros are obtained more energy is lost, so a balance between the two needs to be found [Lees2002; Mulcahy].

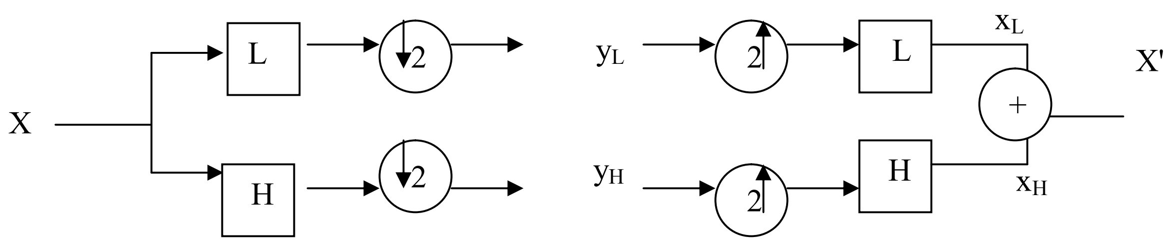
2-Advantages of Wavelet Transform in Data Compression

There are many different forms of data compression. This investigation will concentrate on wavelet transforms. Image data can be represented by coefficients of discrete image transforms. Coefficients that make only small contributions to the information contents can be omitted. Usually the image is split into blocks (subimages) of 8x8 or 16x16 pixels, then each block is transformed separately. However this does not take into account any correlation between blocks, and creates "blocking artifacts" , which are not good if a smooth image is required .

However wavelets transform is applied to entire images, rather than subimages, so it produces no blocking artifacts. This is a major advantage of wavelet compression over other transform compression methods [Lees2002].

3- Wavelets Analysis:

The best way to describe discrete wavelet transform is through a series of cascaded filters. The input image X is fed into low pass filter (L) and high pass filter (H) separately . the output of the two filters are the subsampled. The resulting lowpass subband y_L and high pass subband y_H are shown in figure(1) . the original signal can be reconstructed by synthesis filters (L) and (H) which take the upsampled y_L and y_H as inputs.(for more details see[Ding2007; Mulcahy; Abdulkarim&Ismail2009])



Figure(1) Wavelet decomposition and reconstruction process

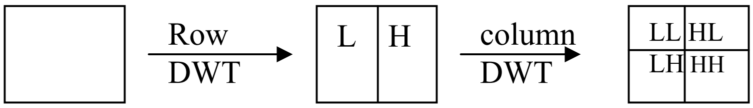
The mathematical representations of y_L and y_H can be defined as :

$$y_L(n) = \sum_{i=0}^{t_L} L(i)X(2n-i) \text{........(1)}$$

$$y_H(n) = \sum_{i=0}^{t_H} H(i)X(2n-i) \text{.........(2)}$$

Where t_L and t_H are the lengths of L and H respectively.

For a two dimensional images , the approach of the 2D implementation of the discrete wavelet transform(DWT) is to perform the one dimensional DWT in row direction and it is followed by a one dimensional DWT in column direction. See figure(2), in the figure, LL is a coarser version of the original image and it contains the approximation information which is low frequency ,LH,HL,and HH are the high frequency subband containing the detail information. Further computations of DWT can be performed as the level of decomposition increases, the concept is illustrated in figure(3), the second and third level decompositions based on the principle of multiresolution analysis show that the LL1 subband shown in figure(3) is decomposed into four smaller subband LL2 ,LH2 ,HL2 ,and HH2 [Ding2007].



Figure(2):2D row and column computation of DWT.

Second level third level

Figure(3): second and third level row and column decomposition.

Numerous filters used to implement the wavelet transform , in present work we used the daudechies filter . whereas , the daubechies basis vectors (forward and inverse transform), for 4x4 segments, are:[Witwit2001]

Low pass: $\frac{1}{4\sqrt{2}}\left[1+\sqrt{3},3+\sqrt{3},3-\sqrt{3},1-\sqrt{3}\right]$

High pass : $\frac{1}{4\sqrt{2}}\left[1-\sqrt{3},\sqrt{3}-3,3+\sqrt{3},-1-\sqrt{3}\right]$

Low $\text{pass}_{\text{inv}}=\frac{1}{4\sqrt{2}}\left[3-\sqrt{3},3+\sqrt{3},1+\sqrt{3},1-\sqrt{3}\right]$

High $\text{pass}_{\text{inv}}=\frac{1}{4\sqrt{2}}\left[1-\sqrt{3},-1-\sqrt{3},3+\sqrt{3},-3+\sqrt{3}\right]$

The representation of f(x,y) at various resolutions can be done by a very simple iteration process. Moreover, the reconstruction of the original function from the coefficients of this representation is equally simple and fast.[Eubanks2007]
Images are treated as two dimensional signals, they change horizontally and vertically, thus 2D wavelet analysis must be used for images. 2D wavelet analysis uses the same 'mother wavelets' but requires an extra step at every level of decomposition.

In 2D, the images are considered to be matrices with N rows and M columns. At every level of decomposition the horizontal data is filtered, then the approximation and details produced from this are filtered on columns.[Lees2002]
At every level, four sub-images are obtained; the approximation(LL), the vertical detail, the horizontal detail and the diagonal detail (LH, HL, HH). As See Figure (3)

4- Wavelet Compression and Thresholding

For some signals, many of the wavelet coefficients are close to or equal to zero. Thresholding can modify the coefficients to produce more zeros. In Hard thresholding any coefficient below a threshold T, is set to zero. This should then produce many consecutive zero's which can be stored in much less space, and transmitted more quickly.
To compare different wavelets, the number of zeros is used. More zeros will allow a higher compression rate, if there are many consecutive zeros, this will give an excellent compression rate.
The energy retained describes the amount of image detail that has been kept, it is a measure of the quality of the image after compression. The number of zeros is a measure of compression. A greater percentage of zeros implies that higher compression rates can be obtained.

The number of zeros in percentage (PoZ) is defined by: [Misiti&Oppenheim2000]

100* (number of zeros of the current decomposition)/ (number of coefficients)

To change the energy retained and number of zeros values, a threshold value is changed. Thresholding can be done globally or locally. Global thresholding involves thresholding every subband (sub-image) with the same threshold value. Local thresholding involves uses a different threshold value for each subband.

5- Wavelet Compression Methodology:

Definition of Wavelet Compression is fix a non negative threshold value T and decree that any detail coefficient in the wavelet transformed data whose magnitude is less than or equal to zero (this leads to a relatively sparse matrix). Then rebuild an approximation of the original data using this doctored version of the wavelet transformed data. In the case of image data, we can throw out a sizable proportion of the detail coefficients in this and obtain visually acceptable results . This process is called lossless compression, When no information is loss (e.g., if T = 0). Otherwise it is referred to as lossy compression (in which case T>0). In the former case, we can get our original data back and in the latter we can build an approximation of it. We have lost some of the detail in the image but it is so minimal that the loss would not be noticeable in most cases.[Raviraj&Sanavullah2007]
Although There are many possible algorithems that indicate an appropriate threshold value [Adams&Patterson2006], so as "trial and error" but this project include finding the best thresholding strategy which compress the image so fastly and The reconstructed image have a good quality as well as preservation of significant image details.

6-Proposed Algorithm and Results:

In our experiments, Different types and different sizes of test images have been used to demonstrate the performance of proposed method . We used the gray scale sample stamp image of size 256x256, satellite image of size 567x674 and medical images of size 256x128.

Matlab numerical and visualization software was used to perform all of the calculations and display all of the pictures in this work.

For one level

1. Read the image .
2. Apply 2D DWT using daubechies wavelet over the image
3. Calculate the STD of original image
4.After decomposing the image and representing it with wavelet coefficients, compression can be perform by ignoring all approximation coefficients below threshold (T=STD).
5.Reconstruct an approximation to the original image by apply the corresponding inverse transform with modified approximation coefficients.
5. The quality of the reconstructed images measured using the error matrices (MSE, PSNR).
6. The same process is repeated for various images.
7. Display the resulting images and comment on the quality of the images.

.-**For multilevels**

1. Read the image
2. Using 2D wavelet decomposition with respect to a daubechies wavelet computes the approximation coefficients matrix CA and detail coefficient matrixes CH, CV, CD (horizontal, vertical & diagonal respectively) which is obtained by wavelet decomposition of the input matrix .
3. From this, again using 2D wavelet decomposition with respect to a daubechies wavelet computes the approximation and detail coefficients which are obtained by wavelet decomposition of the CA matrix. This is considered as level 2.
4. Again apply the daubechies wavelet transform from CA matrix which is considered as CA1 for level 3.
5. Do the same process for level 4,level 5,…
6. Calculate the STD of original image and sets as the threshold value, set all the approximation coefficients to zero except those whose magnitude is larger than STD of image.
7. Take inverse transform for level 1, level 2, level 3,level 4 ….. with only modified approximation coefficients and Reconstruct the images for level 1, level 2, level 3 , level 4…..
9. Display the results of reconstruction 1, reconstruction 2, reconstruction 3, reconstruction 4,…. ie., level 1, 2, 3, 4,…. with respect to the original image.

All results (original images and reconstructed images) are presented in Figs. (4 & 5)

The quantitative test results using proposed method have been tabulated in table(1) for three selected image samples (stamp, satellite and medical images respectively).

The results show that the quantitative results with stamp image are better than satellite and medical images where stamp image yielded higher PSNR values than the other images.

The MSE and PSNR values verify that the compression and reconstruction of the original image are better even at level 6.

Table 1: different types of error matrices (MSE, PSNR) with respect to various compression ratios for various input images.

Image	Level	PSNR	MSE	No. of non zero elements (before compression)	No. of non zero elements (after compression)	Compression Ratio
Stamp image 256x256	1	73.96	0.0026	66451	18115	3.668286
	2	59.29	0.0765	67234	7605	8.840763
	3	54.68	0.22	67502	5160	13.08178
	4	52.19	0.39	67642	4623	14.63162
	5	48.88	0.84	67718	4522	14.97523
	6	43.20	3.11	67762	4506	15.03817
Satellite image 567x674	1	53.12	0.317	384946	127913	3.009436
	2	46.81	1.35	386536	75432	5.124297
	3	43.97	2.60	387168	64086	6.041382
	4	42.24	3.87	387578	61633	6.288482
	5	40.88	5.30	387746	61059	6.35035
	6	39.71	6.94	387858	60950	6.363544
Medical image 256x128	1	47.46	1.167	33186	11307	2.934996
	2	43.61	2.82	33777	6367	5.30501
	3	39.85	6.72	33981	5230	6.497323
	4	35.72	17.42	34089	5019	6.79199
	5	34.20	24.71	34149	4986	6.848977
	6	32.28	38.45	34185	4986	6.856197

7- Discussion and Conclusions

This paper reported is aimed to developing computationally efficient and effective algorithm for lossy image compression using wavelet techniques. So this proposed algorithm developed to compress the image so fastly. The promising results obtained concerning reconstructed image quality as well as preservation of significant image details

The project deals with the implementation of the daubechies wavelet compression techniques and a comparison over various input images. Where involved using Daubechies wavelets and decomposition levels.

These results are substantially better for a stamp image than other utilized images ,where stamp image yielded higher compression ratio and higher PSNR values than others, see table (1).

The wavelet divides the energy of an image into an approximation subsignal, and detail subsignals. Wavelets that can compact the majority of energy into the approximation subsignal ,therefore, the results calculated used global thresholding (threshold=STD of image), it was found to be a fair way of calculating threshold values.

The results proved to be more useful in understanding the effects of decomposition levels ,wavelets and images .Changing the decomposition level changes the amount of detail in the decomposition. Thus, at higher decomposition levels, higher compression rates can be gained. However, more energy of the signal is vulnerable to loss.

The quality of compressed image depends on the number of decompositions. The number of decompositions determines the resolution of the lowest level in wavelet domain.

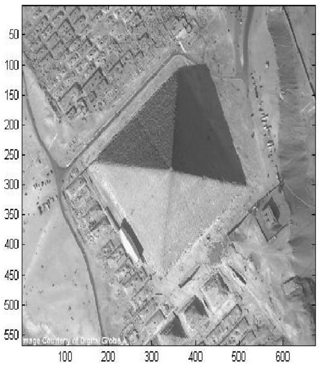
provide the best compression. This is because a large number of coefficients contained within detailed subsignals can be safely set to zero, thus compressing the image. However, little energy should be lost.

Wavelets attempt to approximate how an image is changing, thus the best wavelet to use for an image would be one that approximates the image well.

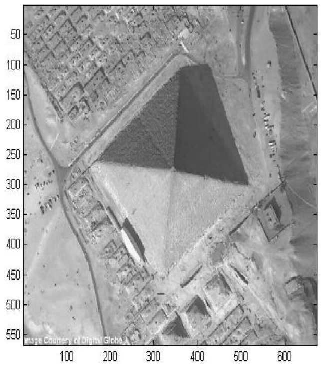
The image itself has a dramatic effect on compression. This is because it is the image's pixel values that determine the size of the coefficients, and hence how much energy is contained within each subsignal. Furthermore, it is the changes between pixel values that determine the percentage of energy contained within the detail subsignals, and hence the percentage of energy vulnerable to thresholding. Therefore, different images will have different compressibilities.

Wavelets are useful for compressing signals but they also have far more extensive uses. They can be used to process and improve signals, in fields such as medical imaging where image degradation is not tolerated they are of particular use. They can be used to remove noise in an image.

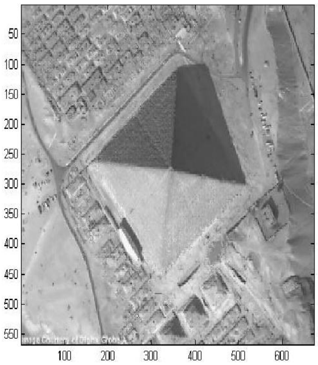
The analysis results have indicated that the performance of the suggested method is a good thresholding strategy, where the constructed images are less distorted.



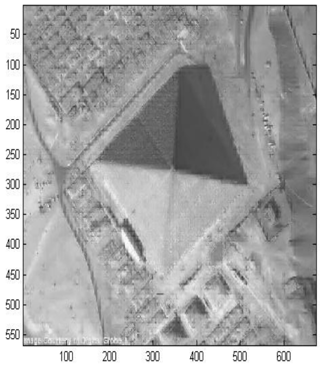
Original image
567x674



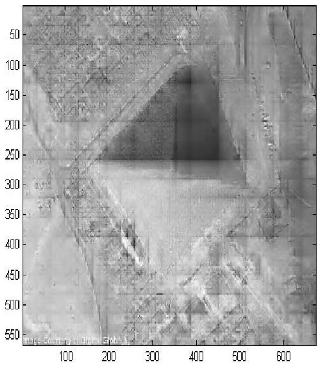
Level -1
PoZ=68.284
PSNR=53.12
MSE=0.317



Level -2
PoZ=82.42
PSNR=46.81
MSE=1.35

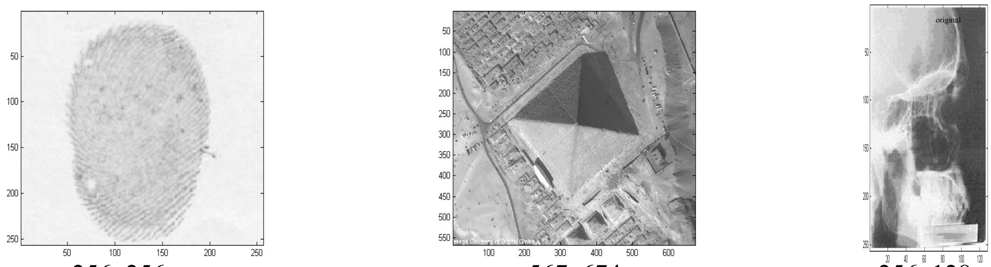


Level -3
PoZ=85.46
PSNR=43.97
MSE=2.60



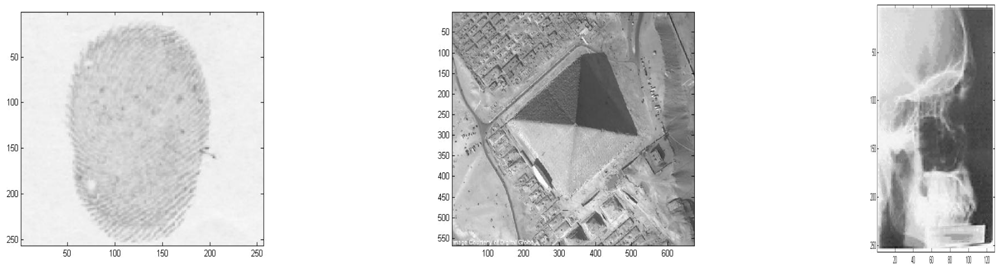
Level -6
PoZ=86.311
PSNR=39.71
MSE=6.94

Fig.(4):Original and reconstructed images at different levels (PoZ is percentage of zeros)



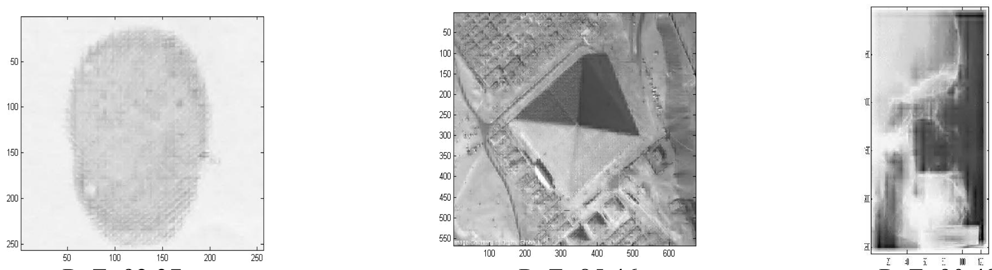
256x256 | 567x674 | 256x128

Original Images



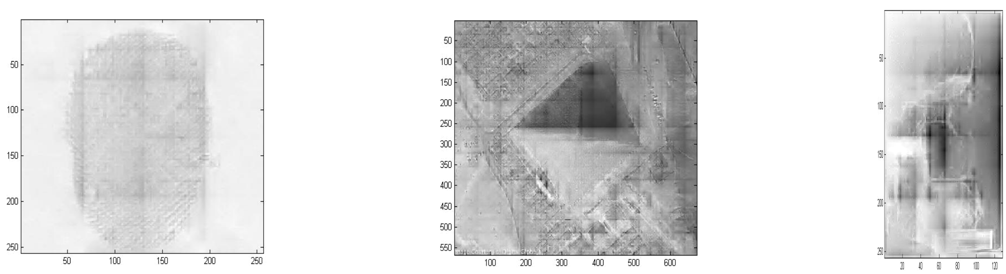
PoZ=72.78	PoZ=68.284	PoZ=70.78
PSNR=73.96	PSNR=53.12	PSNR=47.46
MSE=0.0026	MSE=0.317	MSE=1.167

Reconstructed Images at Level-1



PoZ=92.37	PoZ=85.46	PoZ=90.49
PSNR=54.68	PSNR=43.97	PSNR=39.85
MSE=0.22	MSE=2.60	MSE=6.72

Reconstructed Images at Level-3



PoZ=93.36	PoZ=86.311	PoZ=91.34
PSNR=43.20	PSNR=39.71	PSNR=32.28
MSE=3.11	MSE=6.94	MSE=38.45

Reconstructed Images at Level-6

Fig.(5):Original and reconstructed images at different decomposition levels (PoZ is percentage of zeros)

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